A measure of perceived performance to assess resource allocation

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Abstract Performance measurement is a key issue when a company is designing new strategies to improve resource allocation. This paper offers a new methodology inspired by classic importance–performance analysis (IPA) that provides a global index of importance versus performance for firms. This index compares two rankings of the same set of features regarding importance and performance, taking into account underperforming features. The marginal contribution of each feature to the proposed global index defines a set of iso-curves that represents an improvement in the IPA diagram. The defined index, together with the new version of the diagram, will enable the assessment of a firm's overall performance and, therefore, enhance decision making in the allocation of resources. The proposed methodology has been applied to a Taiwanese multi-format retailer and managerial perceptions of performance and importance are compared to assess the firm's overall performance.

Keywords Performance evaluation · Reasoning under uncertainty · Fuzzy operator · Similarity index

Communicated by V. Loia.

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1 Introduction

Importance–performance analysis (IPA) is considered a major area of research in management sciences (Bacon 2003). Firm features are ranked regarding either their importance or their performance. In general, differences between importance and performance rankings of features are considered when assessing a firm's resource allocation. Initial approaches in the late 1970s were based on simple and intuitive graphic techniques (Martilla and James 1977). Since then, various methodologies have been developed for managerial applications. Specifically, studies in marketing (Fornell et al. 1996; Park et al. 2008), knowledge management and information systems (Ainin and Hisham 2008; Kale and Karaman 2011), operations (Gunasekaran et al. 2004), human resources (Eskildsen and Kristensen 2006) and education (ONeill and Palmer 2004) have recently contributed to the scientific development of IPA. Some current methodologies involve a quantitative approach that leads to a numerical analysis of values obtained from the importance and performance measurements (Globerson 1985).

Ranking systems are commonly used in performance analysis and are considered a main research topic in economics and business when broadly applied to decision-making problems. Many methodologies can be found in the literature to address ranking problems (Butler et al. 2001; Hochbaum and Levin 2006). In some of them, different rankings from the same set of features are compared by means of correlation indexes such as Kendall's tau or Spearman's rho correlation coefficients (Glover et al. 2011; Lapata 2006).

We present in this paper a new similarity index to compare two importance and performance rankings of the same set of features. The proposed index is based on induced ordered weighted averaging (IOWA) operators (Yager and Filev 1999). Rankings are considered as ordered lists of a given set of features or alternatives, and differences between lists are considered to define the index of similarity. This index, when applied to a firm's features rankings for both importance and performance, enables a firm's global performance to be assessed. There are two main differences between our index and existing indexes such as Kendall's tau and Spearman's rho correlation coefficients. On the one hand, the asymmetry of the features treatment, i.e., it just takes into account underperforming features and, on the second hand, the specific relation between the weights and the importance, i.e., the more important an underperforming feature, the greater its weight is considered in the similarity index.

In addition, a new IPA diagram, based on the proposed similarity index is presented to select features where resource allocation is necessary. The "Concentrate Here" region of the new IPA diagram is contained in the corresponding "diagonally-based" region introduced by Abalo et al. (2007), and is defined via the iso-curves obtained when considering the marginal contribution of the features to the proposed similarity index.

An application of the presented methodology to the retail sector has been conducted. The starting point of our application is a set of 44 features used in the retail sector that were selected by expert managers as the main performance variables. Thereafter, a survey of 84 senior managers of a major chain store in Taiwan was undertaken. The survey evaluated the importance and the performance of these features using a Likert scale. The similarity index is applied to compare the two rankings of this set of features. Whilst the proposed similarity index could have broader applications, the specific application in this paper throws light on company resource allocation (Deng 2007).

The paper is organized as follows. The following section presents the state-of-the-art on IPA. Section 3 introduces the new index of similarity between rankings and states its properties. Section 4 presents the real-case application from the retail sector.

A discussion comparing the differences between perceived importance and perceived actual performance enables us to suggest managerial applications for improving resource allocation. Section 5 contains conclusions and suggestions for further research in this area. In addition, two appendixes are included in the paper. Appendix A introduces the absolute order-of-magnitude qualitative model and Appendix B proposes a ranking method based on this model.

2 Literature review on importance–performance analysis

Several approaches for analyzing importance and performance to improve resource allocation have emerged in the literature. In this section, the state of the art in IPA is presented.

The classical IPA was first proposed by Martilla and James (1977) with the objective of evaluating consumer acceptance of a marketing program. As the authors emphasized in their first paper: "It is a low-cost, easily-understood technique that can yield important insights into which aspect of the marketing mix a firm should devote more attention, as well as identify areas that may be consuming too many resources" (Martilla and James 1977). Over the years, IPA has been applied in various fields, importance and performance have been measured in very different ways by many authors, and many approaches and improvements of this technique have been published (Bacon 2003; Deng 2007; Ennew et al. 1993; Eskildsen and Kristensen 2006; Liu et al. 2011).

The traditional IPA methodology basically consists of representing ratings of importance and performance for several features on a two-dimensional chart. The resulting importance–performance grid is divided into four quadrants. To interpret the results, Martilla and James (1977) give a name to each quadrant to help managers determine the highest and lowest priorities for improvement, as shown in Fig. 1.

Inferring priorities from the IPA diagram can be done in various ways, such as the scale-centered quadrant model; the data-centered quadrant model; or the diagonal model. The advantages and disadvantages of each approach are reviewed in Bacon (2003). In the quadrant models, the priorities for improving the features are inferred from the quadrant where each feature is located. In the diagonal model, a diagonal line or lines separate regions and points above the line may represent high priorities for improvement. Some researchers add the examination of the difference between importance and

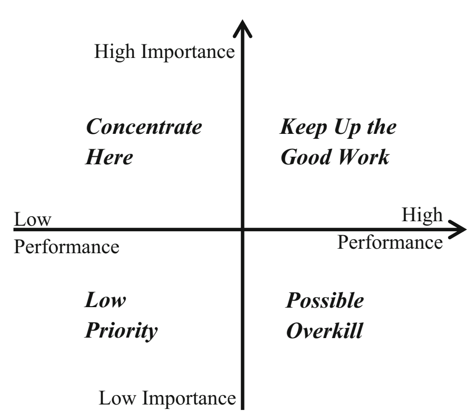

Fig. 1 IPA diagram (Martilla and James 1977)

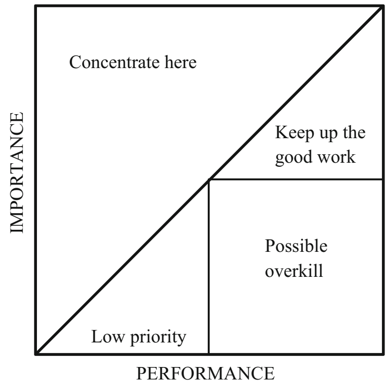

Fig. 2 A partition of the IPA diagram (Abalo et al. 2007)

performance to the grid, known in the literature as "gap analysis". Other authors (Abalo et al. 2007) use a partition that combines the quadrant and diagonal-based schemes, enlarging the top left quadrant as shown in Fig. 2.

A major difficulty facing IPA is the measurement of importance and performance. Direct and indirect measures are found when analyzing different IPA applications (Abalo et al. 2007; Danaher and Mattsson 1994; Wittink and Bayer 1994). Direct measures for both importance and performance can be obtained by asking managers to rank the different attributes; or alternatively, using Likert scales.

Interest in performance measurement has strongly increased over the last 20 years (Taticchi et al. 2010).

Effectiveness and efficiency, according to Neely et al.'s (2005) definitions, have become increasingly important and measurement has been made a key point for enhancing business performance (Sharma et al. 2005). It is relevant to remark that the approach has evolved from being financial based to non-financial based (Motta et al. 2006).

The performance measures should capture the essence of organizational performance (Chen 2002; Gunasekaran et al. 2004). Nevertheless, if the number is too large, the decision-making and control processes may become more difficult (Globerson 1985). In contrast, any single performance measure will present a myopic view that will prevent managers improving overall resource allocation.

Even when the appropriate features have been well identified, it remains necessary to find the best method to measure both the performance and importance of these features. Many authors have tried to find a measure to compare these parameters. In practice, these measures can be obtained using simple comparisons of means, or advanced statistical analysis. Both approaches can be useful in some situations, but both present aggregation problems or are too complex to be operational. An example of an alternative measure can be found in Ennew et al. (1993), where an index to provide a measure of overall satisfaction in service quality is given. In that case, the authors propose an attainment index designed to reflect the extent to which there is a mismatch (confirmation/disconfirmation) between what customers require (importance in our case) and the quality of what they receive (performance in our case).

The aim of this paper is to develop a global index that is simple to use, both in calculating and interpreting the relationship between the importance of the attributes that describe the firm and their perceived performance.

3 An index for comparing importance and performance

Several authors have conducted various analytical measures to individually compare the gap between performance and importance in the features that describe a firm. Nevertheless, there are few contributions that globally capture the overall disparity between importance and performance. As said in Ennew et al. (1993), simple comparison of means at one extreme, and detailed statistical analysis at the other extreme, both offer useful insights but present different types of difficulties: aggregation problems with the comparison of means, and operational problems with techniques such as factor analysis and regression. In Ennew et al. (1993), a set of indexes that measure expectations, perceptions, and overall satisfaction are presented. Nevertheless, this kind of index only takes into account an analysis feature by feature instead of holistically.

As rankings are generated for both importance and performance when measuring the same set of features, the definition of a suitable indicator of their differences is a relevant issue. A comparison of rankings may be undertaken with different techniques, but most techniques do not take into account the relative importance of the ranked items, and only consider their relative ranked position. The index considered in this paper, based on IOWA operator's concept (Chiclana et al. 2007; Yager and Filev 1999), enables importance and performance rankings to be compared more sensitively. IOWA operators were introduced in Yager and Filev (1999) as an extension of ordered weighted averaging (OWA) operators (Yager 1988, 2008).

On the other hand, IOWA operators consider two related variables: first, the order inducing variable, and second, the argument variable. The argument variable values are aggregated using a set of weights based on the order of the values of the first variable.

Definition 1 An IOWA operator of dimension n is a mapping $\Phi: (\mathbb{R}\times\mathbb{R})^n \to \mathbb{R}$ such that (Yager and Filev 1999):

$$\Phi((u_1, x_1), \ldots, (u_n, x_n)) = \sum_{i=1}^{n} w_i x_{\sigma(i)},$$

where $\sigma : \{1, \ldots, n\} \rightarrow \{1, \ldots, n\}$ is a permutation such that $u_{\sigma(i)} \geq u_{\sigma(i+1)}$, $\forall i = 1, \ldots, n-1$, and w_i are a set of weights such that $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$.

Both OWA and IOWA operators have been deeply studied and applied in multi-criteria and group decision-making literature (Chiclana et al. 2007). In addition, several extensions of the above-mentioned operators have been introduced in other studies to deal with situations where fuzzy or linguistic variables are considered in decision-making processes (Herrera and Herrera-Viedma 1997; Herrera-Viedma et al. 2006).

The following definitions consider differences between performance and importance in features ordered from the most important to the least. The global index proposed in this paper is a convenient weighted mean of these differences; i.e., an IOWA operator with importance as order inducing variable and these differences as argument variable.

Let n be the number of features considered to describe a firm and I_i and P_i be the importance and performance positions in the rankings of the ith feature, respectively. I_i and P_i are numbers from 1 to n such that the feature corresponding to $I_i = 1$ is the most important and the feature corresponding to $P_j = 1$ is the best performed.

Note that from now on, the features are considered ordered with respect to their importance position in the ranking, i.e., the (i)th feature is the feature with importance position in the ranking $I_{(i)} = i$, and so $I_{(1)} = 1, \ldots, I_{(n)} = n$.

Definition 2 The *importance–performance vector of a firm* F is the vector:

$$\mathrm{IPR}(F) = ((1, P_1), \ldots, (n, P_n))$$

whose components are the pairs of ranking values of its features with respect to importance and performance, ordered according to their importance in the ranking.

The n components of the $\mathrm{IPR}(F)$ vector of a firm F can be represented as points in the IPA diagram, each point (x, y) corresponding to one of the n considered features. To include all these n points in the classical IPA diagram, the reverse positions in the ranking with respect to performance and importance, centered in $\left(\frac{n+1}{2}, \frac{n+1}{2}\right)$, have to be computed, i.e., $x = \frac{n+1}{2} - P_i$ and $y = \frac{n+1}{2} - i$.

Example 1 To illustrate the representation of the importance–performance vector of a firm on the IPA diagram, let us consider a case with $n = 7$ features and two firms F^1 and F^2. Let

$$\mathrm{IPR}(F^1) = ((1, 5), (2, 2), (3, 4), (4, 1), (5, 6), (6, 7), (7, 3))$$
$$\mathrm{IPR}(F^2) = ((1, 3), (2, 7), (3, 5), (4, 6), (5, 1), (6, 4), (7, 2))$$

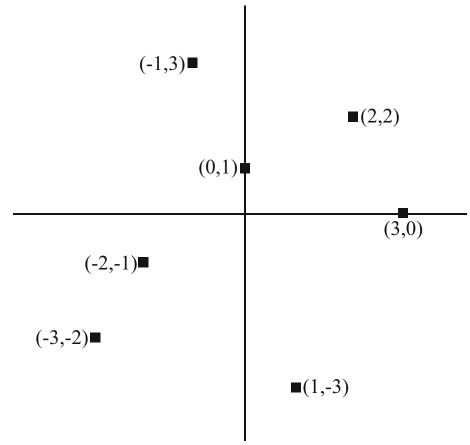

Fig. 3 $\mathrm{IPR}(F^1)$ in the IPA diagram

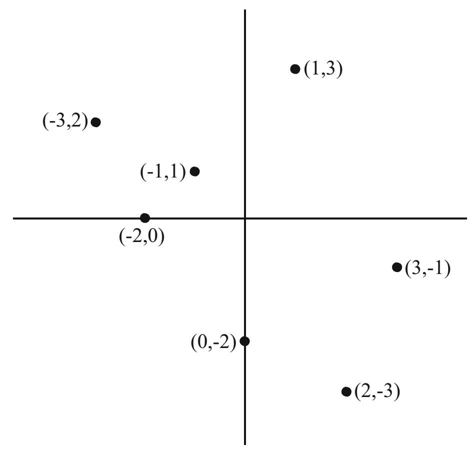

Fig. 4 $\mathrm{IPR}(F^2)$ in the IPA diagram

be the importance–performance vectors of F^1 and F^2. The representation on the IPA diagram of $\mathrm{IPR}(F^1)$ and $\mathrm{IPR}(F^2)$ is depicted in Figs. 3 and 4, respectively.

Note that the ranking values (i, P_i) of the considered features with respect to importance and performance can be obtained via any ranking method. Appendix B proposes a ranking method based on the absolute order-of-magnitude qualitative model resumed in Appendix A.

From now on, let us denote by IPR^* the importance–performance vector of the ideal best performed firm, i.e., $\mathrm{IPR}^* = ((1, 1), \ldots, (i, i), \ldots, (n, n))$ and IPR_* the importance–performance vector of a firm in the opposite situation, i.e., $\mathrm{IPR}_* = ((1, n), \ldots, (i, n-i+1), \ldots, (n, 1))$.

To focus on the features in which resources must be allocated, and from the importance–performance vector of a firm $\mathrm{IPR}(F) = ((1, P_1), \ldots, (n, P_n))$, the next definition introduces a new vector that takes into account only underperforming features, i.e., those features where their performance position in the ranking is worse than their importance position in the ranking.

Definition 3 Let $\mathrm{IPR}(F) = ((1, P_1), \ldots, (n, P_n))$ be the importance–performance vector of a firm F. The *non-negative performance–importance differences vector of the firm* is the n-dimensional vector $\mathrm{DV}(F) = (X_1, \ldots, X_n)$, where $X_i = \max(P_i - i, 0)$, for all $i = 1, \ldots, n$.

Note that for any firm F, the components of $\mathrm{DV}(F)$, are $X_i \geq 0$ for all $i = 1, \ldots, n$ and nonzero components correspond to underperforming features.

In the two cases described above, corresponding to the ideal best performed firm and its opposite situation, the associated non-negative performance–importance differences vectors are, respectively,

$$\mathrm{DV}^* = (0, \ldots, 0) \quad \text{and}$$
$$\mathrm{DV}_* = (n-1, \ldots, \max(n-2i+1, 0), \ldots, 0).$$

Based on the usual partial order in $\mathbb{R}^n$, the next definition establishes a preference relation between differences vectors introduced in Definition 3 and, therefore, between the importance–performance status of firms.

Definition 4 Let $\mathrm{DV}(F^1) = (X_1^1, \ldots, X_n^1)$ and $\mathrm{DV}(F^2) = (X_1^2, \ldots, X_n^2)$ be two differences vectors, then $\mathrm{DV}(F^1)$ *is preferred to* $\mathrm{DV}(F^2)$, $\mathrm{DV}(F^1) \preceq \mathrm{DV}(F^2)$, when $\mathrm{DV}(F^1) \leq \mathrm{DV}(F^2)$ with the usual order in $\mathbb{R}^n$, i.e., $X_i^1 \leq X_i^2$ for all $i = 1, \ldots, n$.

In this way, $\mathrm{DV}(F^1)$ is preferred to $\mathrm{DV}(F^2)$ when F^1 performs better than F^2 for all underperforming features. Differences vectors introduced in Definition 3 enable us to define an index via an IOWA operator that preserves this preference relation:

Definition 5 Let $\mathrm{DV}(F) = (X_1, \ldots, X_n)$ be the differences vector of a firm, the *Global importance–performance Index* ($\mathcal{G}$) of the firm is:

$$\mathcal{G}(X_1, \ldots, X_n) = \sum_{i=1}^{n} w_i X_i$$

where weights are computed using Borda–Kendall method (Kendall 1948), i.e., $w_i = \frac{2(n-i+1)}{n(n+1)}$ for all $i = 1, \ldots, n$.

Note that $w_i \in [0, 1]$ for all $i = 1, \ldots, n$ and $\sum_{i=1}^{n} w_i = 1$. These weights express the ratio between the reverse importance position in the ranking $n - I_i - 1 = n - i - 1$ of the ith feature and $\sum_{i=1}^{n} i$. Indeed, the weights decrease from $\frac{2n}{n(n+1)}$ to $\frac{2}{n(n+1)}$. In this way, features with greater importance have greater weights in the weighted mean defining the $\mathcal{G}(X_1, \ldots, X_n)$ of a given firm.

Note that $\mathcal{G}(X_1, \ldots, X_n)$ is an IOWA operator with importance as order inducing variable and the non-negative performance–importance differences as argument variable.

In the following proposition, some properties of $\mathcal{G}(X_1, \ldots, X_n)$ are provided.

Proposition 1 *$\mathcal{G}(X_1, \ldots, X_n)$ satisfies the following properties:*

1. $\mathcal{G}(X_1, \ldots, X_n) \geq 0$.
2. $\mathcal{G}(X_1, \ldots, X_n) = 0$ *if and only if* $P_i = i$ *for all* $i = 1, \ldots, n$, *i.e.,* $(X_1, \ldots, X_n) = (0, \ldots, 0) = \mathrm{DV}^*$.
3. *If n is even* $\mathcal{G}(\mathrm{DV}_*) = \frac{5n-2}{12}$, *and if n is odd* $\mathcal{G}(\mathrm{DV}_*) = \frac{(n-1)(5n+3)}{12n}$.
4. $\mathcal{G}(X_1, \ldots, X_n)$ *preserves the* $\preceq$ *relation.*

Proof 1. Considering that $X_j \geq 0, w_j \geq 0$ and $\sum_{j=1}^{k} w_j = 1$, we obtain: $w_j X_j \geq 0$, therefore, $\mathcal{G}(X_1, \ldots, X_n) \geq 0$.
2. Let us prove $[\mathcal{G}(X_1, \ldots, X_n) = 0 \Rightarrow (P_i = i \ \forall i = 1, \ldots, n)]$: $\mathcal{G}(X_1, \ldots, X_n) = 0 \Rightarrow (X_i = 0 \ \forall i) \Rightarrow (P_i \leq i \ \forall i) \Rightarrow (P_i - i \leq 0 \ \forall i)$. If j exists such that $P_j < j$, then $P_j - j < 0$ which leads to $\sum_{i=1}^{n}(P_i - i) < 0$ and which contradicts the fact that $\sum_{i=1}^{n} P_i = \sum_{i=1}^{n} i$. The proof of $\Leftarrow$ is straightforward.
3. In the case n is even: the components of the vector of non-negative performance–importance differences are $X_i = n-2i+1, \ i = 1, \ldots, \frac{n}{2}$, and $X_i = 0, \ i = \frac{n}{2}+1, \ldots, n$. Therefore,

$$\mathcal{G}(\mathrm{DV}_*) = \sum_{P_i \geq i} \frac{2(n-i+1)}{n(n+1)}(P_i - i)$$
$$= \frac{2}{n(n+1)} \sum_{i=1}^{n/2} (n-i+1)(n-2i+1),$$

which leads, after a straightforward calculation, to: $\mathcal{G}(\mathrm{DV}_*) = \frac{5n-2}{12}$.
In the case n odd: the components of the vector of non-negative performance–importance differences are $X_i = n - 2i + 1, \ i = 1, \ldots, \frac{n-1}{2}$, and $X_i = 0, \ i = \frac{n-1}{2} + 1, \ldots, n$. Therefore,

$$\mathcal{G}(\mathrm{DV}_*) = \sum_{P_i \geq i} \frac{2(n-i+1)}{n(n+1)}(P_i - i)$$
$$= \frac{2}{n(n+1)} \sum_{i=1}^{(n-1)/2} (n-i+1)(n-2i+1),$$

which leads, after a straightforward calculation, to: $\mathcal{G}(\mathrm{DV}_*) = \frac{(n-1)(5n+3)}{12n}$.

Table 1 Marginal contribution of features to $\mathcal{G}(\mathrm{DV}(F^1))$ and $\mathcal{G}(\mathrm{DV}(F^2))$

$\mathrm{IPR}(F^1)$	Marginal contribution	$\mathrm{IPR}(F^2)$	Marginal contribution
(1, 5)	1	(1, 3)	0.5
(2, 2)	0	(2, 7)	1.071
(3, 4)	0.179	(3, 5)	0.357
(4, 1)	0	(4, 6)	0.286
(5, 6)	0.107	(5, 1)	0
(6, 7)	0.071	(6, 4)	0
(7, 3)	0	(7, 2)	0
$\mathcal{G}$ index	1.357	$\mathcal{G}$ index	2.214

4. The proof is straightforward. □

Example 2 Continuing with Example 1, the differences' vectors and the global importance–performance indexes corresponding to firms F^1 and F^2 are, respectively,

$$\mathrm{DV}(F^1) = (4, 0, 1, 0, 1, 1, 0), \quad \mathcal{G}(\mathrm{DV}(F^1)) = 1.357;$$
$$\mathrm{DV}(F^2) = (2, 5, 2, 2, 0, 0, 0), \quad \mathcal{G}(\mathrm{DV}(F^2) = 2.214,$$

which leads us to infer that firm F^1 performs better than firm F^2 (see Proposition 1, Property 4).

Note that in this case, the maximum possible value for the global index would be $\mathcal{G}(\mathrm{DV}_*) = 2.714$. Table 1 shows the marginal contribution of each feature, as given in Definition 5, to the $\mathcal{G}$ index, i.e., the product $w_i X_i$, being $i = 1, \ldots, 7$ for both firms.

Although the most important feature of F^1 has a bad performance, most of the non-negative performance–importance differences are smaller for $\mathrm{IPR}(F^1)$ than for $\mathrm{IPR}(F^2)$.

The following proposition establishes an intuitive property for the $\mathcal{G}$ index, relating it with the partition of the IPA diagram in Abalo et al. (2007) (see Fig. 2) and determining relevant importance–performance situations.

Proposition 2 *The features that contribute to the $\mathcal{G}$ index are all features above the principal diagonal of the IPA diagram, i.e., those classified as "Concentrate Here" in the partition of the IPA diagram in* Abalo et al. (2007).

Proof The proof is straightforward, because only features above the diagonal $I = P$ provide non-negative performance–importance differences. □

The following proposition determines the level curves (iso-curves) of the marginal contribution of the features to the $\mathcal{G}$ index in the IPA diagram, giving decision makers precise information about where to concentrate resources to improve performance.

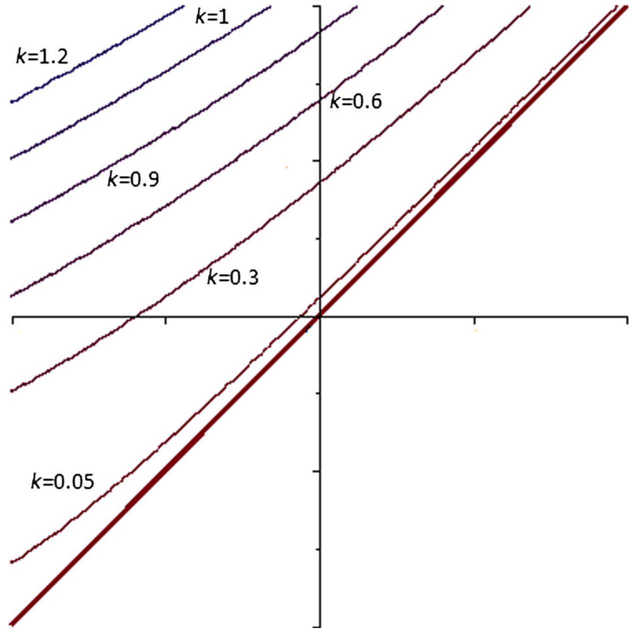

Fig. 5 Level curves of the marginal contribution of the features to the $\mathcal{G}$ index

Proposition 3 *The level curves of the marginal contribution of a feature to the $\mathcal{G}$ index in the IPA diagram are*:

$$\frac{n+1+2y}{n(n+1)}(y-x) = k,$$

for any $k \in \mathbb{R}^+$ (see Fig. 5).

Proof Let us consider, as in Figs. 3 and 4 representation, $x = \frac{n+1}{2} - P_i$ and $y = \frac{n+1}{2} - i$. From Definition 5, the level curves' equations of the marginal contribution of the ith feature to the $\mathcal{G}$ index are:

$$\frac{2(n-i+1)}{n(n+1)}(P_i - i) = k,$$

for all features with non-negative performance–importance difference (otherwise, the features do not contribute to the $\mathcal{G}$ index). By substituting P_i and i by their expressions in terms of x and y, respectively, we obtain:

$$\frac{2\left(n - \left(\frac{n+1}{2} - y\right) + 1\right)}{n(n+1)}\left(\left(\frac{n+1}{2} - x\right) - \left(\frac{n+1}{2} - y\right)\right) = k,$$

which is equivalent to:

$$\frac{2n - (n+1-2y) + 2)}{n(n+1)}(y-x) = k.$$

Finally,

$$\frac{n+1+2y}{n(n+1)}(y-x)=k.$$

□

Figure 5 shows the level curves of the marginal contribution of the underperforming features to the $\mathcal{G}$ index over the IPA diagram partition in Abalo et al. (2007). Features in the same level curve are those with the same degree of underperformance, i.e., for each k, the corresponding level curve contains features "with degree of under-performance k". In Fig. 5, level curves corresponding to $k = 0.05, 0.3, 0.6, 0.9, 1$ and 1.2 are represented.

This representation clearly improves the approach in Abalo et al. (2007) to determine the target features for resource allocation. The "Concentrate Here" zone of the diagram can be dynamically selected depending on the available resources and the admitted level of underperformance.

Example 3 Continuing with Examples 1 and 2, Figs. 6 and 7 include the features that are contributing to the $\mathcal{G}$ index in each of the two firms together with the level curves of the marginal contribution discussed in Proposition 3.

Figures 6 and 7 show that the marginal contribution of features in the case of firm F^2 are bigger than those corresponding to F^1. The level curves in Figs. 6 and 7 highlight the features where resources must be allocated as a priority in each firm.

Two are the main differences between the $\mathcal{G}$ index and other well-known correlation coefficients defined to compare rankings. On the one hand, the $\mathcal{G}$ index takes into account only underperforming features. On the other hand, since the $\mathcal{G}$ index is defined through an IOWA operator applied to the

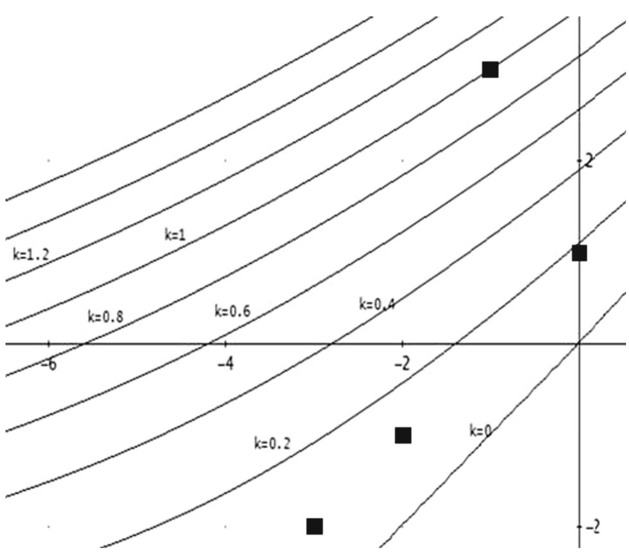

Fig. 6 IPR(F^1) in the IPA diagram

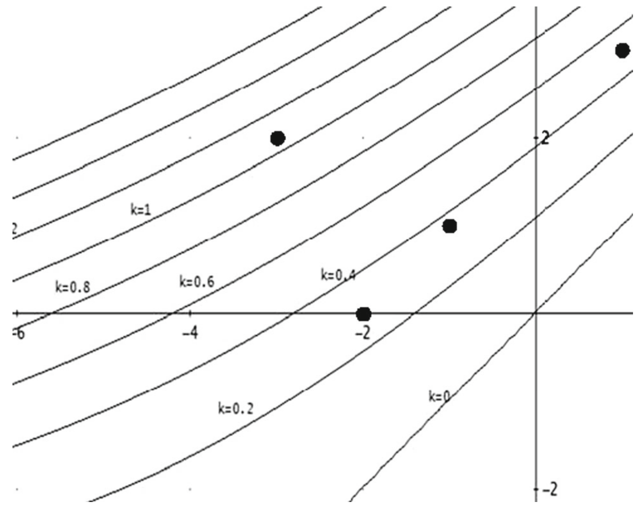

Fig. 7 IPR(F^2) in the IPA diagram

non-negative performance–importance differences of a firm, not all the features contribute to it in the same way. The more underperforming and the more important a feature is, the greater its contribution to the $\mathcal{G}$ index.

Let us highlight the advantages and disadvantages of our proposal in comparison with other existing IPA approaches. The IPA framework has been widely accepted due to its simplicity of calculations and intuitive graphical representation. From a computational point of view, the proposed methodology represents an improvement since the marginal contribution of each feature to the $\mathcal{G}$ index is determined. These marginal contributions provide information about how the current performance of a firm can be improved by giving decision makers information about where to concentrate resources. From a graphical point of view, the innovative contribution of the proposed approach is that features can be drawn in a new diagram with the level curves of the marginal contribution of each feature to the $\mathcal{G}$ index, so managers can easily identify those underperformed features that require immediate action.

As a limitation of the proposed methodology, we can note that the $\mathcal{G}$ index compares the importance and performance of features just within a particular company. While, in a situation of limited information about competitors, it provides managers a framework to work with and to explore the strengths and weaknesses of the company; nevertheless, the proposed methodology including the $\mathcal{G}$ index could be improved by adding measures of features' performance based on comparisons of products and services of either competing companies or the sector. In this direction, some extensions of IPA are reviewed in Kim and Oh (2001). In particular, some approaches modify the original IPA by considering three or more dimensions, being competitors' performance one of them. These studies consider, instead of the four quadrants in the original IPA grid, either eight octants or even more dif-

Table 2 Comparison of different IPA approaches

	Graphical model	Grid dimensionality	Global measurement
Martilla and James (1977)	Quadrant based	2	No
Abalo et al. (2007)	Diagonal based	2	No
Burns (1986)	Quadrant based	3	No
Dolinsky (1991)	Quadrant based	3	No
Keyt et al. (1994)	Quadrant based	4	No
Ortinau et al. (1989)	Vertical lines	2	Qualitative
Proposed method	Level curves	2	Numerical

ferent outcomes' areas. However, adding dimensions in the IPA grid implies loosing simplicity of attribute display and data interpretation.

In Table 2, an analysis and comparison are given of the main features of some of the existing IPA extensions and the method presented. The three considered characteristics to compare them are: the graphical approach considered, the dimensions of the IPA diagram, and finally the use of an index or indicator measuring global performance.

In general, in decision-making aid systems, one should note that there is no single method which outperforms all other methods in all aspects. However, the simplicity in user interaction is, indeed, one of the main values that share most of the IPA methods, and it is closely related to the grid dimensionality.

4 A real-case application to the retail sector

In this section, an application of the proposed methodology to assess importance–performance in a Taiwan retail company is presented, after a brief introduction to the performance evaluation framework for the retail sector.

4.1 Evaluating performance in the retail sector

In recent years, the role of knowledge within strategic management has become the subject of substantial advances in research (Braz et al. 2011; Chini 2004; Gherardi 2009; Nonaka and Teece 2001; Teece 2000). Nevertheless, most of these studies relate to aspects of the transfer of knowledge rather than the application of knowledge in the evaluation of performance.

Despite the relative paucity of research in a retail context, the use of expert knowledge by managers is an important factor at a micro-level in the success of retailers and at the macro-level for sectorial re-structuring. Managers bring to bear their individual expert knowledge to solve problems at operational and strategic levels in the retail firm. The knowledge they hold and apply depends mainly on their perceptions of the levels of current performance and the levels of importance of specific features. An issue that arises, deriving from this view of the diversity of knowledge held by retail managers, is how to synthesize the individual perceptions of managers in ways that can be useful in strategic management. Thus, aggregating managerial opinions on the relative performance of some specific features and analyzing the contribution of these different features to the overall performance of the retailer are considered crucial.

In this research context, these individual and differing perceptions of the relevance of the various resources can be gathered through qualitative data collection. Given that managers will view differently the relative importance of the various features, a method to compare the opinions of managers and synthesize these qualitatively framed opinions would be useful.

In the next subsections, we conduct a full experiment that first includes the selection of relevant performance-related variables. Second, we present a survey of senior managers that measures their perceptions of the importance and performance of the selected variables, based on the order-of-magnitude qualitative model as included in Appendix A. Thirdly, the ranking method detailed in Appendix B is applied to obtain rankings of the selected variables, aggregating expert opinions with respect to importance and performance, respectively. Finally, the global index $\mathcal{G}$, together with the iso-curves of the feature contribution to the index introduced in Sect. 3, is used to summarize the differences in these rankings and identify features to which resources should be allocated.

4.2 Design of the empirical study and data collection

A study involving senior managers as experts was undertaken in a major chain store organization. President Chain Store Corporation is a multinational retailer based on Taiwan that operates a multi-format strategy through a range of organizational structures. It is the largest retailer in Taiwan. Using literature surveys and 25 in-depth interviews with a cross section of retailer stake-holders, 170 performance-related variables relevant to retailing were identified. From this list, after rationalization and classification in terms of the nature

Table 3 The resource attributes used as variables in the evaluation procedures

Resource area	Resource concept	Feature
Physical resource	Reach ability	1. Number of customer visits
		2. Store location
Legal resource	Brand strength	3. Sales of private brand products
		4. Social responsibility
Human resource	Human management	5. Employee turnover rate
		6. Staff training
Organizational resource	Expansion ability	7. Franchise system
		8. Store opening strategy
	Productivity	9. Sales per store
		10. Spending-per-visit rate
	General management	11. Internal procedures
		12. Achievement of year-end goals
	Technology management	13. Investments in technology development
		14. Quality of data collection and process sys.
	Organizational management	15. Empowerment of staff
		16. Response to staff issues
	Inventory management	17. Inventory loss control
		18. Inventory service level
	Marketing management	19. Market positioning
		20. Store renovation/redecoration
	Financial management	21. Expense control ability
		22. Percentage of part-time staff
	Product innovation	23. Shelf-life of new products
		24. Speed of new products development
	Loan repay ability	25. Past credit history
		26. Financial support from stockholders
		27. Internet channel development
	Diversification	28. Maintaining target customers in market diversification
Informational resources	Market segment risk	29. Following fashion trends
		30. Facing seasonal demands
	Strategic vision	31. Openness to criticism
		32. Willingness to innovate
Relational resources	Stakeholder relations	33. Customer complaints management
		34. Cost sharing with suppliers on promotions
		35. Joint venture opportunity with compets.
External factors	Actions from outside stakeholders	36. Changes in customer preferences
		37. Changes in supplier contract content
		38. Innovation and imitation from competitors
	Political environmental	39. Change in government laws
		40. Stability of government
	Technological environmental	41. Innovation of new technology equipment
		42. New management system software devel.
	Socio-culture environmental	43. Change of population structure
		44. Change of lifestyle

of the resource, 44 features or variables related to resources used in retailing were selected as the main performance variables. The selection was undertaken by reference to the views of interviewees and research literature on resource-based theories of the firm. Seven resource areas were established within these 44 features, as shown in Table 3.

A survey was then undertaken with managers in the Taiwan head office. Data were collected from 84 senior managers across all the managerial functions. Managers were divided into five main groups depending on broad functional area: marketing (15); operations and store operations (17); accounting, finance and audit (24); R&D and information systems (14); and other (e.g., human resources, law) (14).

Managers were asked to use their expertise to assess each of the 44 variables in terms of their perceived importance to the performance of the firm. An ordinal scale of 1–4 was used as: (1) extremely important; (2) very important; (3) moderately important; (4) not very important; with (5) as "don't know". The managers were asked to repeat the exercise in terms of the perceived performance of the firm based on the same variables, with the scale being: (1) extremely good (or extremely strong); (2) very good (or very strong); (3) moderately good (or moderately strong); (4) not very good (or not very strong); with (5) again used as "don't know".

4.3 Data analysis and results

This subsection is devoted to analyzing and comparing the evaluations of importance and performance of the 44 features in Table 3. Using the ranking methodology described in Appendix B, the features were ranked with respect to their importance and with respect to their performance from the responses from all 84 experts.

In this case, the non-negative performance–importance differences vector of the firm is the 44-dimensional vector:

$$\begin{aligned} \mathrm{DV}(F) = (&10, 12, 1, 4, 10, 13, 13, 0, 3, 16,\\ &0, 0, 10, 27, 14, 0, 0, 12, 3, 0, 6, 11, 1, 0, 0, 10, 16,\\ &0, 0, 1, 0, 7, 0, 3, 0, 0, 0, 0, 3, 0, 0, 0, 1, 0). \end{aligned}$$

Then, weights are computed using Borda–Kendall law, obtaining $w_i = \frac{45-i}{990}$ for all $i = 1, \ldots, 44$. With these values, the $\mathcal{G}$ index introduced in Sect. 3 to compare rankings with respect to importance and performance is computed and produces a global importance–performance index $\mathcal{G}(\mathrm{DV}(F)) = 6.329$. Taking into account that the ideal best performing firm has $\mathcal{G}(\mathrm{DV}^*) = 0$ and the firm in the opposite situation has $\mathcal{G}(\mathrm{DV}_*) = 18.167$, as proven in Proposition 1, there is, therefore, a significant divergence between the two considered rankings (corresponding to about one third of the range of variation, precisely a 34.8 %). This fact shows that there is room for resource allocation improvement. Note that, similar conclusions can be obtained when we compute other well-known correlation coefficients, such as Kendall's tau or Spearman's rho, for the same pairs of importance–performance rankings. In these two cases, we obtain 0.378 and 0.506, respectively.

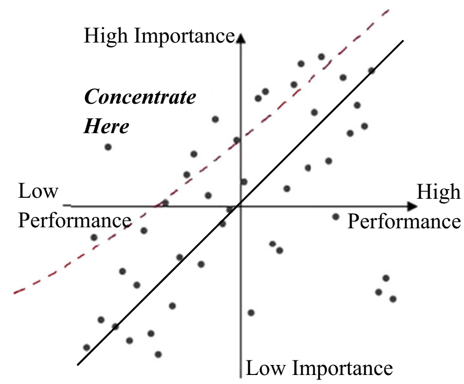

Fig. 8 Comparison of importance and performance rankings from expert managers' perceptions

The comparison of the two rankings given by our methodology and shown in Fig. 8 also points out the directions for this improvement. The added value of our contribution to the comparison of both rankings is the combination of the $\mathcal{G}$ index and the level curves of the marginal contribution of the features to this index. In Fig. 8, an example of the level curve corresponding to $k = 0.3$ is depicted (see Proposition 3).

As detailed in Proposition 2, among the 44 features selected, the 24 features that plot above the principal diagonal are those that contribute to the $\mathcal{G}$ value of the firm. These are aspects of the firm that are perceived by managers as underperforming and coincide with aspects in the "Concentrate Here" region defined in Abalo et al. (2007). Similarly, Fig. 8 shows the region labeled as "Concentrate Here" in the Martilla's classical IPA diagram, which contains *seven* features.

In addition, in this paper, as explained in Sect. 3, we propose a step forward in understanding which features may be improved. Beyond the IPA diagram, we suggest concentrating resources in those features that contribute most to the $\mathcal{G}$ value of the firm. In Fig. 8, these features have been visualized over the dotted line for the case $k = 0.3$. This line is the iso-curve of the marginal contribution of the features to the $\mathcal{G}$ index in the IPA diagram corresponding to $k = 0.3$ (see Proposition 3). Visually, most of the contribution to the $\mathcal{G}$ index can be seen as focusing on a limited number of features. These ten extreme values are listed in Table 4.

Most are directly or indirectly associated with firm growth. Six out of the ten relate directly to organizational resources, three relate to physical, human, and relational resources, respectively, and the final one relates to external factors. Note that in this case, the value $k = 0.3$ has been used; however, depending on the available resources, different values of k could be considered.

Table 4 Variations in the ranking of expert managers when importance is ranked much higher than performance

Features	Ranking of importance	Ranking of performance	Contribution to $\mathcal{G}$
Market positioning	1	11	0.444
Number of customer visits	2	14	0.521
Customer complaints management	5	15	0.404
Sales per store	6	19	0.512
Store opening strategy	7	20	0.499
Franchise system	10	26	0.566
Spending-per-visit rate	13	23	0.323
Staff training	14	41	0.845
Quality of data collection and process system	15	29	0.424
Innovation of new technology equipment	18	30	0.327

4.4 Discussion and managerial implications

Hansen and Bush (1999) pointed out that IPA is a simple and effective technique that can assist in identifying improvement priorities. IPA has been applied as an effective means of evaluating a firm's competitive position in the market, identifying improvement opportunities, and guiding strategic planning efforts. However, typically, managers must work with limited resources in competitive business environments. For this reason, the proposed method, able to decide how to best allocate scarce resources to maximize importance–performance, is very helpful.

The results of the empirical testing of the methodology show how to identify areas of perceived underperformance of the firm. In our real case, 44 features related to resources used in retailing were selected as main performance variables. Managers in the President Chain Store Corporation then evaluated the perceived importance and the perceived performance of the firm for these 44 features. From these evaluations, the features were ranked with respect to these two concepts using the ranking methodology described in Appendix B. The proposed $\mathcal{G}$ index is computed, and the iso-curves of the marginal contribution of the features to the $\mathcal{G}$ index enabled recognition of the perceived underperforming features of the firm. The methodology used, by taking into account the qualitative perceptions held by managers, provides a useful tool for decision making for the retailer.

Considering the iso-curve of the marginal contribution to the $\mathcal{G}$ index as corresponding to a contribution of $k = 0.3$, ten features appeared as being underperforming in that firm; thus, they can potentially be improved. This level of contribution ($k = 0.3$) corresponds, as a percentage, to 4.7 % of the $\mathcal{G}$ index. As we can see in Table 2, the "staff training" feature, which belongs to the human resources area, is perceived as the most underperforming feature, contributing more than 13 % ($0.13351 = 0.845/6.329$) to the $\mathcal{G}$ index. There are seven features whose contribution to the $\mathcal{G}$ index varies between 6.4 and 9 %, with two features contributing about 5.1 % each. The remaining underperforming features, below the considered iso-curve, contribute <4.7 % each to the $\mathcal{G}$.

As stated, when modifying the value of k, a different number of features for focus would be obtained. The strength of the methodology proposed is its adaptable nature, which helps managers to improve the efficiency of the firm. Therefore, the $\mathcal{G}$ index could be considered as a valuable decision-support tool to better allocate resources within the firm.

5 Conclusions and future research

This paper contributes to improving IPA by providing a new measure that captures the overall relationship between importance and performance. This measure is obtained by considering the relevant features that describe a firm and so enable a firm's managers to improve decision-making in resource allocation. The developed methodology, together with a new version of the classical IPA diagram, enables managers to assess a firm's overall performance and detect features where resources should be allocated. The presented global importance–performance index ($\mathcal{G}$), inspired by OWA operators, is a weighted sum of the non-negative performance–importance differences, where weights depend on the importance of the feature.

Moreover, the $\mathcal{G}$ index also leads to an enhancement of the IPA diagonal-based scheme with a new representation: Contribution-to-$\mathcal{G}$ iso-curves. These level curves show a more accurate picture of the most-needed-investment features, and determine a new "Concentrate Here" zone in the classical IPA diagram. A real-case application in the retail sector has been used to show that the presented methodology can lead to a more accurate IPA of a firm's situation. The real-case application gives us an example of how $\mathcal{G}$ could benefit managerial decision-making processes in resource allocation.

As future work, a marginal sensitivity analysis of the $\mathcal{G}$ index incorporating changes in resource allocation would be a major future contribution for decision-making processes. It could be of interest in a more advanced study of $\mathcal{G}$ properties to determine the upper-boundary of the index for relative comparisons of company performances. Additional analysis that separately considers the functional area of managers could be performed to infer how the area of expertise influences perceptions and modifies the $\mathcal{G}$ index.

Acknowledgments This work was partially supported by the SENSORIAL Research Project (TIN2010-20966-C02-01, 02), funded by the Spanish Ministry of Science and Information Technology.

Appendix A: The qualitative absolute order-of-magnitude model

Qualitative reasoning techniques, specifically order-of-magnitude models, are considered an appropriate mathematical framework to represent expert opinions or preferences through a hierarchical model with linguistic labels (Andrés et al. 2010; Soto 2011; Herrera et al. 2008).

The one-dimensional absolute order-of-magnitude qualitative model (Agell et al. 2012; Travé-Massuyès and Dague 2003) works with a finite number of qualitative labels corresponding to an ordinal scale of measurement. The number of labels chosen to describe a real problem is not fixed, but depends on the characteristics of each represented variable.

Let us consider an ordered finite set of *basic labels* $S_m^* = \{B_1, \dots, B_m\}$, which is totally ordered as a chain: $B_1 < \dots < B_m$, each basic label corresponding to a linguistic term, for instance, "very bad" < "bad" < "acceptable" < "good" < "very good". The *complete universe of description* for the order-of-magnitude space OM(m), with granularity m, is the set $\mathbb{S}_m = \mathbb{S}_m^* \cup \{[B_i, B_j] \,|B_i, B_j \in S_m^*, i < j\}$, where the labels $[B_i, B_j]$ with $i < j$ are defined $[B_i, B_j] = \{B_i, B_{i+1}, \dots, B_j\}$ and named *non-basic labels* (see Fig. 9).

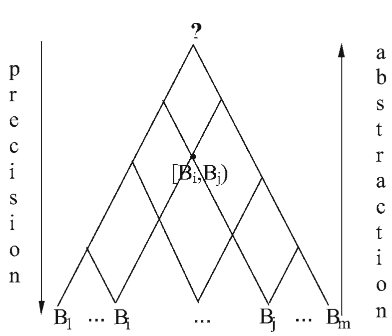

Fig. 9 The complete universe of description $\mathbb{S}_m$

The order considered in the set of basic labels S_m^* induces a partial order $\leq$ in $\mathbb{S}_m$ defined as:

$$[B_i, B_j] \leq [B_r, B_s] \Longleftrightarrow \left(B_i \leq B_r \text{ and } B_j \leq B_s\right), \qquad (1)$$

considering the convention $[B_i, B_i] = B_i$.

This relation is trivially an order relation in $\mathbb{S}_m$, but a partial order, since there are pairs of non-comparable labels. Moreover, as Fig. 9 shows, there is another partial order relation in $\mathbb{S}_m$ "to be more precise than"; given two qualitative labels X_1 and X_2 in $\mathbb{S}_m$, we say that X_1 is *more precise than* X_2 if $X_1 \subsetneq X_2$. The least precise label (most abstract description) is $? = [B_1, B_m]$ and basic labels are the most precise labels.

Appendix B: A ranking method using qualitative linguistic descriptions

In the proposed ranking method, each feature is characterized by the judgments of k evaluators, and each evaluator makes his/her judgements by means of qualitative labels belonging to an order-of-magnitude space $\mathbb{S}_{m_h}$ with granularity m_h for $h = 1, \dots, k$. The evaluations are then synthesized by means of the distance to a reference k-dimensional vector of labels. This reference k-dimensional label is given by the supreme of the sets of evaluations of each feature. The distances between evaluations and their supreme give the ranking of features directly. In this way, the process considered for ranking features assessed by k expert evaluators can be split in the following four steps:

1. Representing features as k-dimensional vectors of labels.
2. Defining a distance d between k-dimensional vectors of labels.
3. Building a reference k-dimensional vector of labels $\mathbf{X}^{\text{sup}}$.
4. Obtaining the ranking of the features from the values $d(\mathbf{X}, \mathbf{X}^{\text{sup}})$.

The subsections below describe each of the above steps.

B.1. Feature representation as k-dimensional vectors of labels

Features are represented by a k-dimensional vectors of labels belonging to the set $\mathbb{X}$, which is defined as:

$$\mathbb{X} = \mathbb{S}_{m_1} \times \dots \times \mathbb{S}_{m_k} = \big\{\mathbf{X} = (X_1, \dots, X_k) | X_i \in \mathbb{S}_{m_h} \\ \forall h = 1, \dots, k\big\}. \qquad (2)$$

For every component, monotonicity is assumed, i.e., $X_h \leq X'_h$ indicates that the evaluation made by the evaluator h corresponding to the feature X' is better or equal to the one corresponding to X. The order relation defined in each $\mathbb{S}_{m_h}$ is extended to the Cartesian product $\mathbb{X}$:

$$\mathbf{X} = (X_1, \ldots, X_k) \leq \mathbf{X}' = (X'_1, \ldots, X'_k) \iff X_h \leq X'_h \quad \forall h = 1, \ldots, k. \tag{3}$$

This order relation in $\mathbb{X}$ is partial, since there are pairs of non-comparable k-dimensional vectors of labels. And $\mathbf{X} < \mathbf{X}'$, that is to say, $\mathbf{X} \leq \mathbf{X}'$ and $\mathbf{X} \neq \mathbf{X}'$, means that feature $\mathbf{X}$ is preferred to feature $\mathbf{X}'$ by all the evaluators.

B.2. A distance between k-dimensional vectors of labels

A method for computing distances between k-dimensional vectors of labels is presented in Agell et al. (2012) via a codification of the labels in each $\mathbb{S}_{m_h}$ given by a location function. The location function codifies each element $X_h = [B_i, B_j]$ in $\mathbb{S}_{m_h}$ by a pair of integers $(l_1(X_h), l_2(X_h))$, where $l_1(X_h)$ is the opposite of the number of basic elements in $\mathbb{S}_{m_h}$ that are "between" B_1 and B_i, that is, $l_1(X_h) = -(i-1)$, and $l_2(X_h)$ is the number of basic elements in $\mathbb{S}_{m_h}$ that are "between" B_j and B_{m_h}, i.e., $l_2(X_h) = m_h - j$.

The extension of the location function to the set $\mathbb{X}$ of k-dimensional vectors of labels is defined in the following way:

$$L(\mathbf{X}) = L(X_1, \ldots, X_k) = (l_1(X_1), l_2(X_1), \ldots, l_1(X_k), l_2(X_k)). \tag{4}$$

A distance d between labels $\mathbf{X}, \mathbf{X}'$ in $\mathbb{X}$ is then defined via a weighted Euclidian distance in $\mathbb{R}^{2k}$ between their codifications:

$$d(\mathbf{X}, \mathbf{X}') = \sqrt{\sum_{h=1}^{k} w_h[((l_1(X_h) - l_1(X'_h))^2 + (l_2(X_h) - l_2(X'_h))^2]}. \tag{5}$$

where w_i are considered to be the weights assigned to the k evaluators and $\sum_{h=1}^{k} w_h = 1$. This function inherits all the properties of the weighted Euclidian distance in $\mathbb{R}^{2k}$.

B.3. Building a reference k-dimensional vector of labels

The reference k-dimensional vector of labels considered in this ranking method is the supreme with respect to the order relation $\leq$ of the set of feature representations.

Let $\{\mathbf{X}^1, \ldots, \mathbf{X}^n\} \subset \mathbb{X}$ be the set of n features representations to be ranked, then the supreme of the set $\mathbf{X}^{\text{sup}}$, i.e., the minimum label in $\mathbb{X}$ which satisfies $\mathbf{X}^r \leq \mathbf{X}^{\text{sup}}, r = 1, \ldots, n$, is computed as follows:

Given $\mathbf{X}^r = (X^r_1, \ldots, X^r_k)$, with $X^r_h = [B^r_{i_h}, B^r_{j_h}]$ for all $h = 1, \ldots, k$, and for all $r = 1, \ldots, n$, then,

$$\mathbf{X}^{\text{sup}} = \sup\{\mathbf{X}^1, \ldots, \mathbf{X}^n\} = (\tilde{X}_1, \ldots, \tilde{X}_k),$$

where:

$$\tilde{X}_h = [\max\{B^1_{i_h}, \ldots, B^n_{i_h}\}, \max\{B^1_{j_h}, \ldots, B^n_{j_h}\}]. \tag{6}$$

B.4. Obtaining the features ranking from the values $d(\mathbf{X}, \mathbf{X}_{\text{sup}})$

Let d be the distance defined in $\mathbb{X}$ in Formula (5) and $\mathbf{X}^{\text{sup}}$ the reference label defined in Formula (6). Then, the following binary relation in $\mathbb{X}$:

$$\mathbf{X} \ll \mathbf{X}' \iff d(\mathbf{X}', \mathbf{X}^{\text{sup}}) \leq d(\mathbf{X}, \mathbf{X}^{\text{sup}}) \tag{7}$$

is a pre-order, i.e., it is reflexive and transitive. This pre-order relation induces an equivalence relation $\equiv$ in $\mathbb{X}$ by means of:

$$\mathbf{X} \equiv \mathbf{X}' \iff [\mathbf{X} \ll \mathbf{X}' \,,\; \mathbf{X}' \ll \mathbf{X}] \iff d(\mathbf{X}', \mathbf{X}^{\text{sup}}) = d(\mathbf{X}, \mathbf{X}^{\text{sup}}). \tag{8}$$

In the quotient set $\mathbb{X}/\equiv$, the following relation between equivalence classes is:

$$\text{class}\,(\mathbf{X}) \trianglelefteq \text{class}\,(\mathbf{X}') \iff \mathbf{X} \ll \mathbf{X}' \iff d(\mathbf{X}', \mathbf{X}^{\text{sup}}) \leq d(\mathbf{X}, \mathbf{X}^{\text{sup}}) \tag{9}$$

is an order relation. It is trivially a total order.

In this way, a set of features $\mathbf{X}^1, \ldots, \mathbf{X}^n$ can be ordered as a chain with respect to their proximity to the supreme: class $(\mathbf{X}^{i_1}) \trianglelefteq \cdots \trianglelefteq$ class $(\mathbf{X}^{i_n})$.

If each class $(\mathbf{X}^{i_j})$, $j = 1, \ldots n$, contains only a feature representation $\mathbf{X}^{i_j}$, the process is finished and we obtain the ranking $\mathbf{X}^{i_1} \trianglelefteq \cdots \trianglelefteq \mathbf{X}^{i_n}$. If there is some class $(\mathbf{X}^{i_j})$ with more than one feature representation, then the same ranking process is applied to the set of the feature representations belonging to class $(\mathbf{X}^{i_j})$, and continued until an iteration of the process gives the same ranking as the previous iteration. The final ranking $\mathbf{X}^{m_1} \trianglelefteq \cdots \trianglelefteq \mathbf{X}^{m_n}$ is then obtained.

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